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6. AUTHOR(S)
Professor Johnathan P. How

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Massachusetts Institutue of Technology
77 Massachusetts Ave
Cambridge, MA 02139

8. PERFORMING ORGANIZATION REPORT NUMBER

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The objective of this research was to develop algorithms that can be embedded in a hierarchic coordination and control architecture for teams of multiple UAVs. This resulted in several algorithms that use mixed-integer linear programming (MILP) to perform the activity and path planning components of the team coordination problem. Research on this project focused on implementing these approaches using a receding planning horizon to improve the computational tractability and on increasing the robustness of the techniques to uncertainty in the situational awareness. We have also completed a multi ~ LTAV testbed that will be used to evaluate various distributed and hierarchic control architectures.

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FINAL REPORT

CONTROL ARCHITECTURE DESIGN FOR COOPERATIVE CONTROL

AFOSR # F49620-01-1-0453

Jonathan P. How
Space Systems Laboratory
Department of Aeronautics and Astronautics
Massachusetts Institute of Technology

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Abstract

The objective of this research was to develop algorithms that can be embedded in a hierarchic coordination and control architecture for teams of multiple UAVs. This resulted in several algorithms that use mixed-integer linear programming (MILP) to perform the activity and path planning components of the team coordination problem. Research on this project focused on implementing these approaches using a receding planning horizon to improve the computational tractability and on increasing the robustness of the techniques to uncertainty in the situational awareness. We have also completed a multi-UAV testbed that will be used to evaluate various distributed and hierarchic control architectures.

Main Accomplishments

The following lists the main accomplishments of the project:

- Developed a new receding horizon formulation of the task assignment (RHTA) problem using the decomposition approach [1, 2]. The RHTA selects multiple tasks for each UAV during each iteration of the design, which enables greater coordination between the team and can result in much better performance than iterative greedy assignment techniques. This faster task assignment algorithm forms the core of the hierarchic coordination architecture using "dynamic sub-teams".
- Modified the MILP trajectory design algorithm to: (i) execute as a model predictive controller; (ii) account for external disturbances (e.g., impact of wind on the UAVs); and (iii) use improved linearized models of the UAV dynamics. Validated the trajectory design using a team of three rovers [3] and a hardware-in-the-loop simulation of five UAVs [4, 5].
- Extended the cooperative path planning algorithm (RH-MILP) to 3D [6, 7]. Modified the formulation to include models of the environment risk in the cost-to-go, glue, and detailed paths. Developed a new pruning technique that significantly reduces the computation time of the receding horizon algorithm. This approach is faster, but it still retains the freedom to choose between multiple future paths and has been shown to work well in practice [8, 9, 10, 11].
- Developed a novel approach to the decentralized collision avoidance problem for multiple UAVs using our new robust model predictive controller [3, 12]. This decentralized Model Predictive Controller (DMPC) algorithm guarantees robust satisfaction of coupling constraints

and offers a significant computation improvement over a centralized approach. The key point is that, while the vehicles are assumed to communicate, the solution process does not iterate, so it scales well with the fleet size [13, 14].

- The task assignment algorithms have been extended to add robustness to uncertainty in the situational awareness. The receding horizon task assignment (RHTA) has been extended to solve problems with coupled reconnaissance and strike objectives [22, 15]. We have also developed a new Filter-embedded Task Assignment (FETA) algorithm that gives a formal method of reducing the impact of disturbances or uncertainty in the cost estimates in the on-line task assignment [2, 16].
- Completed the design of the DURIP-funded multi-rover and multi-UAV testbeds and performed initial flight tests of the path planning algorithms on the UAVs [4, 5, 9, 10, 11, 17].

Algorithm Details

With many vehicles, obstacles, and targets, the coordination of a fleet of Unmanned Aerial Vehicles (UAVs) is a very complicated optimization problem, and the computation time typically increases very rapidly with the problem size. Previous research proposed an approach to decompose this large problem into task assignment and trajectory design problems, while capturing key features of the coupling between them. This enabled the control architecture to solve an assignment problem first to determine a sequence of waypoints for each vehicle to visit, and then concentrate on designing paths to visit these pre-assigned waypoints. Refs. [2, 5] discusses the extension of that approach to the Receding Horizon Task Assignment (RHTA) algorithm. RHTA was modified further so that it can be executed in real-time when the situational awareness is changing rapidly. The calculation was sped up by using Concert Technology™ by ILOG [18] to avoid the slow process of transferring data between different parts of the solution algorithm and by using an incremental algorithm to generate updates to the cost map as the knowledge of the environment changes.

Task Assignment Algorithms: Work on this project also investigated the role of uncertainty in task assignment algorithms, leading to robust techniques that mitigate the effects on the command and control decisions. This uncertainty could result from inherent sensing errors, incorrect prior information, loss of communication with teammates, or adversarial deception. Our analysis showed that there are very close similarities between the various robust optimization methods that have recently been proposed (including techniques based on interval uncertainty models [19] and the CVaR approach [20]), suggesting that comparable levels of robustness and performance could be achieved using a very simple algorithm [21]. With this insight, we developed a new version of the robust task assignment that is computationally tractable and yields levels of robustness that are similar to the more sophisticated algorithms that are not suitable for real-time applications [15, 19].

RHTA was also extended to include reconnaissance tasks that can be added to a mission to reduce the uncertainty in the environment. The optimal strike/reconnaissance mission, which explicitly captures the coupling between performing reconnaissance tasks and reducing the uncertainty in the associated strike tasks, is nonlinear, but with a change of variables we showed that it can be solved as a MILP [15, 22].

We also developed a modified formulation of the task assignment that can be used to tailor the control system to mitigate the effect of noise in the situational awareness (SA) on the solution [16]. The approach taken here is to perform the reassignments at the rate the information is updated, which enables the planner to react immediately to any significant changes that occur in the environment. Also, rather than just limiting the rate of change of the plan, this new approach embeds

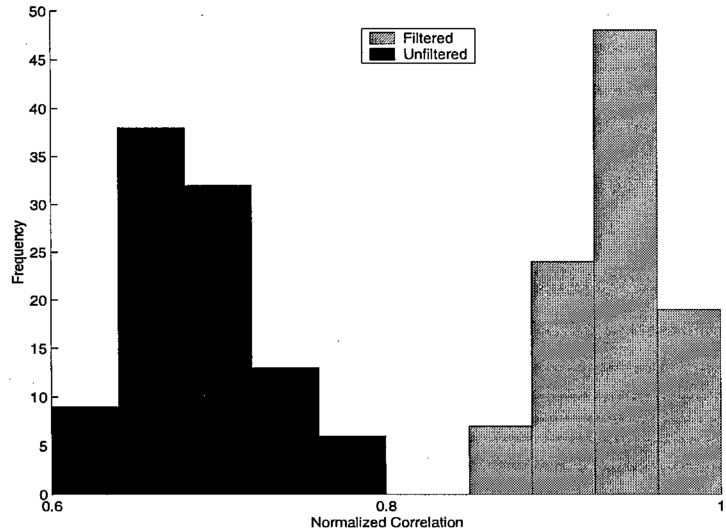

Fig. 1: *Comparison of the plan correlation over time with and without filtering. The higher correlation of the new algorithm shows that the plans change much less dramatically as a result of changes in the information available to the planner.*

a more sophisticated filtering operation in the task assignment algorithm. We have shown that this modified formulation can be interpreted as a noise rejection algorithm that reduces the effect of the high frequency noise on the planner. A key feature of this filter-embedded task assignment algorithm is that the coefficients of the filter are tuned online using the past information. Fig. 1 shows that adding our filtering tends to increase the correlation between plans from one time-step to the next, which decreases the variation in the plans. This means that the task assignment is returning the same solution even though the data in the problem is changing slightly due to noise/disturbances/uncertainty in the cost estimates. The unfiltered results show lower correlation, which means the plans are changing and the vehicles would be re-assigned to new tasks (each plan might be optimal at that time-step, but this can lead to a "churning" type of behavior wherein the vehicles flip back and forth between assignments [23].)

We have also addressed the problem of weapon target assignment in a risky environment [24]. Two formulations were developed. The first is simple to solve, but the objective function ignores the effect that the tasks performed by some of the weapons can have on the risk/performance of the other weapons. The resulting targeting process is shown to be *coordinated*, but because it ignores this interaction, it is what we call *non-cooperative*. The second formulation accounts for this interaction and solves for the optimal *cooperative* strategy using Dynamic Programming. Two approximation methods were investigated for these cooperative problems, and these are shown to achieve near-optimal solutions with computation times that are suitable for on-line implementation. The results from numerous simulations clearly show the benefits of cooperative strategies over just coordinated ones [24].

MILP for Path Planning: References [6, 7, 8, 25] outline our path planning approach which uses MILP to compute a short, detailed trajectory around obstacles, no-fly-zones, and other vehicles using an estimate of the cost-to-go from a shortest path algorithm. The research in this project extended this receding horizon approach (called RH-MILP) in several ways:

- Developed a new formulation of RH-MILP for 3D paths [7]. The approach is similar to our previous 2D algorithms that construct a coarse cost map to provide approximate paths from a sparse set of nodes to the goal and then use MILP optimization to design the detailed part of the trajectory. The cost map calculation was modified to account for possible vertical vehicle maneuvers [7].

- Embedded a new pruning algorithm in RH-MILP to significantly reduce the computation time [6]. The approach is much faster, but it still retains the flexibility to choose better paths around obstacles, and has been shown to work well in practice [4, 9, 11].

- Included environmental uncertainty/risk in the RH-MILP cost-to-go. Developed a new algorithm for approximately solving robust shortest path problems (called ARSP) that yields levels of performance that are comparable to previously published algorithms, but is significantly faster (only approximately 2.5 times the computational effort to solve the nominal problem) [17].

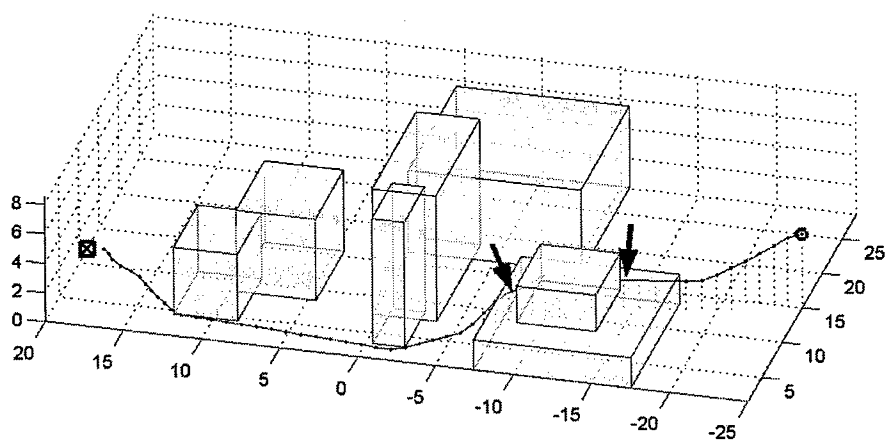

Fig. 2: *Three dimensional trajectory in a complicated environment with risks using a mid-level weighting on altitude.*

Fig. 2 shows an example scenario for the 3D RH-MILP. With a low penalty on altitude, the vehicle just flies over all of the obstacles so that the resulting trajectory is effectively a straight line connecting the start and goal. With a very large altitude penalty, the vehicle avoids climbing over any of the obstacles and simply flies around them at a very low altitude – the 2D solution. Fig. 2 shows a trajectory with medium penalty, for which the vehicle flies around the larger obstacles, but decides to fly over the first-story of the two-story obstacle near the start of the trajectory (which is directly in the way), skirting around the outside of the second story.

Model Predictive Control: Receding horizon control is often referred to as *Model Predictive Control* (MPC), and our other research has developed MPC formulations in a more general setting, with applications to the RH-MILP problem. In particular, we have developed a new robust MPC (RMPC) approach that uses *constraint tightening* [26] with a more general candidate policy, thereby leading to a less constrained optimization and hence a less conservative controller [12, 13]. The approach retains "margin" for future feedback action, which becomes available to the MPC optimization as time progresses. Since robustness follows only from the constraint modifications, only nominal predictions are required, avoiding both the large growth in problem size associated with incorporating multivariable uncertainty in the prediction model and the conservatism associated with worst case cost predictions, a common alternative.

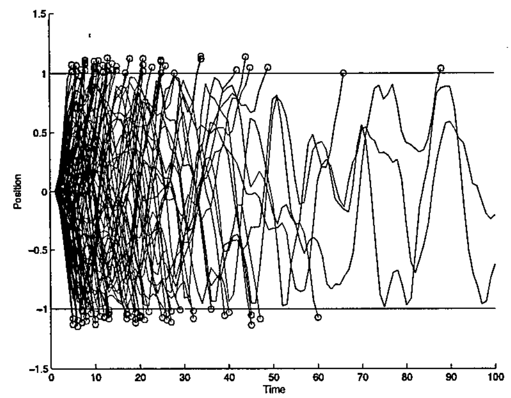

Fig. 3: *Non-robust.*

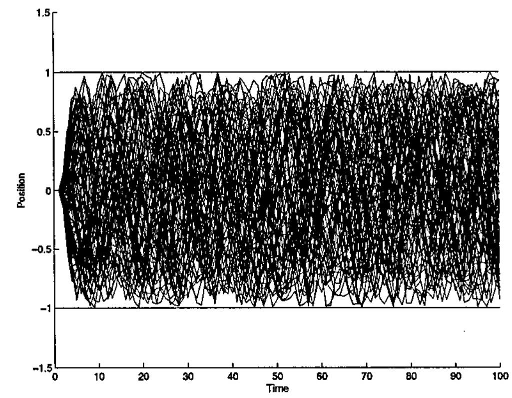

Fig. 4: *Robust.*

Fig. 3 shows position time histories for 100 simulations of a double integrator system using nominal MPC. The position constraint is shown dashed, the control was constrained to have unit magnitude or less and a random disturbance of up to 20% of the control was included. Each o marks the end of a simulation as the problem became infeasible. Fig. 4 shows the same results using robust MPC with constraint tightening. Observe that the position goes right to the constraint but never crosses it, remaining feasible throughout.

<u>Decentralized MPC</u> The same concept has been used to develop a decentralized MPC (DMPC) algorithm for multiple subsystems with hard, coupled constraints. Multiple UAVs with collision avoidance constraints form an example of this class of systems [13, 14]. The algorithm scales much better than a centralized approach as each subsystem has an individual planning optimization solving *only* for its own actions. The actions of other subsystems are accounted for by communication, but feasible solutions are guaranteed and it is not necessary to iterate between subsystems to check feasibility. The subproblems are solved sequentially, and constraint tightening is employed to ensure that each subproblem has at least one feasible solution, given a feasible solution to the preceding subproblem.

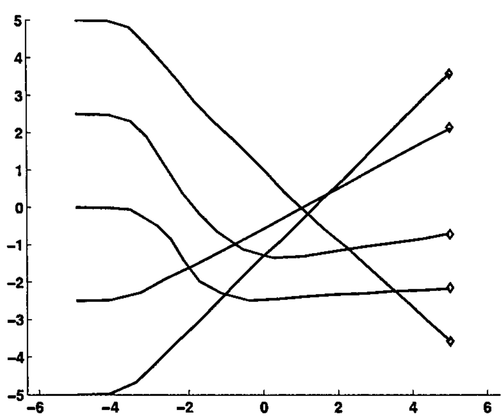

Fig. 5: *Typical DMPC scenario.*

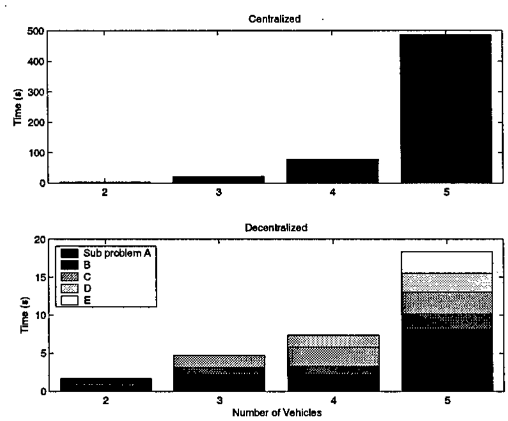

Fig. 6: *DMPC Computation comparison*

To demonstrate the improvement in scalability, DMPC was applied to a multi-UAV collision avoidance problem – 50 random instances were done for each fleet size and compared with centralized robust MPC for the same problems. Fig. 5 shows a typical scenario. The median solution times are shown in Fig. 6. Note the different scales on the upper and lower plots, and that the decentralized solution times are broken down by subproblem but shown stacked, as they are solved sequentially. For 5 vehicles, computation time was improved by a factor of 20 or more [14].

The DMPC algorithm was also extended to explicitly account for delays in the system, arising from both the computation of each control optimization and the communication between vehicles. The algorithm was demonstrated in hardware, using wheeled robot vehicles (Fig. 7) to emulate UAVs. MILP optimization was used in real-time within the DMPC algorithm to solve the nonconvex trajectory optimizations. Fig. 8 shows trajectories from experiments using three rovers. In the first figure, the target boxes are at the bottom right, and rover 1 must change its path significantly to avoid collisions. The last two plots show a different scenario, in which rovers 1 and 3 must swap positions and rover 2 crosses both their paths. In these cases, all the rovers take indirect paths to avoid collisions. These experimental results confirmed that the modified algorithm can operate successfully in the presence of realistic computation and communication delays.

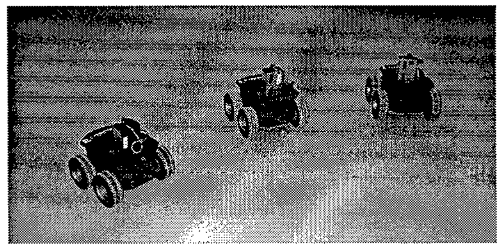

Fig. 7: *Three rover experimental setup.*

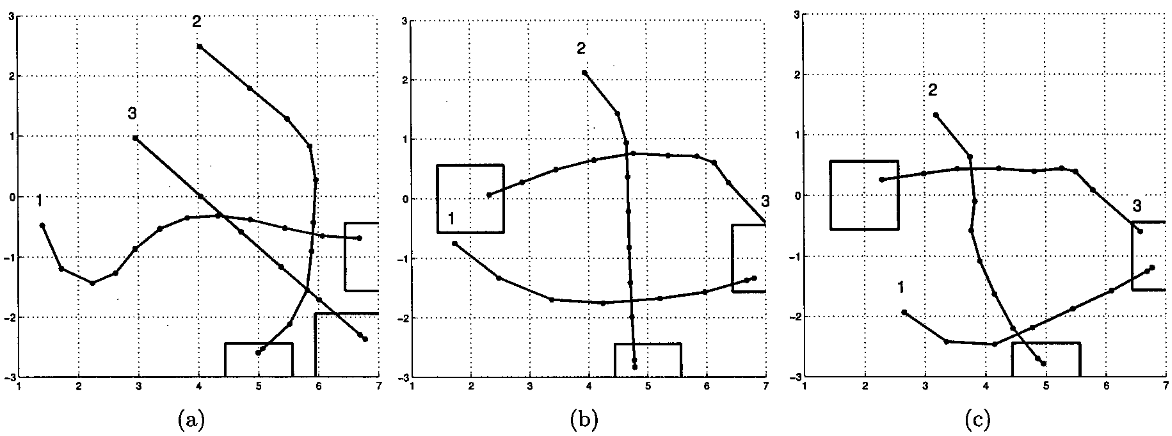

Fig. 8: *DMPC Results for Three Rovers. Numbers mark the starting points of each rover and the target regions are shown by boxes.*

UAV Testbed Demonstrations

The UAV testbed shown in Fig. 9 was developed to validate and evaluate the coordination and control approaches [5, 10]. This work was motivated by the observation that a key step towards transitioning these high-level algorithms to future missions will be to successfully demonstrate that they can handle similar challenges on scaled vehicles operating in realistic environments. A wireless video system was integrated with the UAV testbed to produce high quality images from the airborne vehicles. Fig. 10 shows a typical aerial shot from one of the UAVs. This system is used to track stationary and moving objects on the ground and provide feedback to the operator. The status at the end of the project was:

- UAV testbed has been operated autonomously on numerous (> 40) occasions [4]. Fig. 11 shows the results of a 22 min. autonomous flight involving two UAVs simultaneously flying

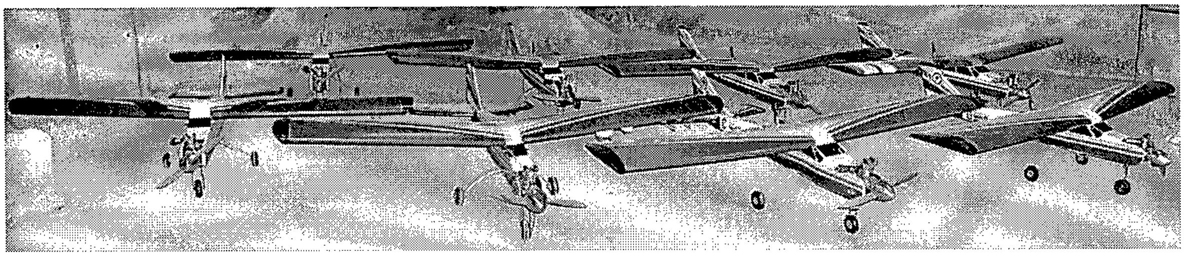

Fig. 9: *UAV testbed with 8 identical aircraft.*

Fig. 10: *Image from onboard video.*

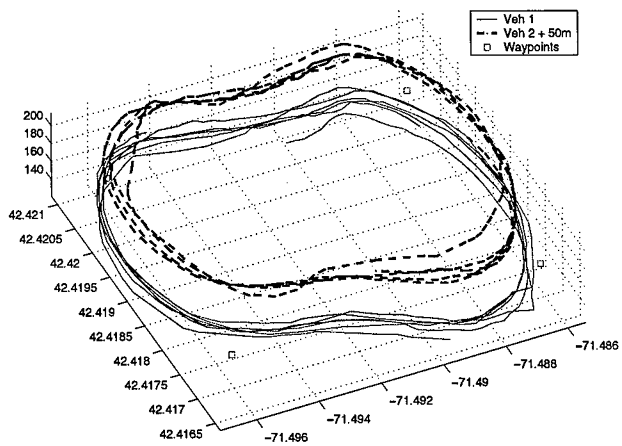

Fig. 11: *Data from 2 UAVs on same plan. 50m offset applied for easier viewing.*

the same flight plan. Both vehicles tracked the waypoints in the presence of wind and open loop formation flight was achieved by adjusting the commanded speed until the vehicles were in phase with one another. A 50m vertical offset was applied to the data to allow for easier viewing.

- Implemented RH-MILP on the UAVs [4, 10, 11]. The results were successful, but they highlighted the need to account for the effect of wind disturbances on the entire planning system. This also requires that the plans be robust to flight time uncertainty and that the planner can rapidly adapt to variations in the execution.
- Developed a flexible GUI for designing mission scenarios, which is a challenging problem when there are many vehicles and targets and the environment is dynamic. The interface can be used to layout the scenario prior to the mission. It can also be used during the mission to provide the operator with a visualization of the current plan, enabling them to interact with the optimization algorithms [17].

Personnel Supported

Professor Jonathan How; graduate students E. King and M. Alighanbari; and undergraduates C. Wesley and C. Engel; and Staff Pete Young.

Transitions

There have been several key transitions of the technology as part of this program:

- Key interactions with Robert Miller at Northrop Grumman (Oct 2003–present).
- Working with Jerry Wohletz, Kathleen Misovec, and Jorge Tierno at AlphaTech (now BAE) from Jan 2004 – June 2005 on an STTR (phase-1).
- Our MILP path planning algorithm were successfully demonstrated on the Boeing OCP platform as part of the DARPA SEC program [27, 28].
- Dr. A. Richards (former student) is now a Lecturer in Controls and Dynamics, Dept. of Aerospace Engineering, University of Bristol

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